Automated Training Plan Generation For Athletes

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***Abstract*—In sports, athletes need detailed and individualised training plans for maintaining and improving their skills in order to achieve their best performance in competitions. This presents a considerable workload for coaches, who besides setting objectives have to formulate extremely detailed training plans. Automated Planning, which has already been successfully deployed in many real-world applications such as space exploration, robotics, and manufacturing processes, embodies a useful mechanism that can be exploited for generating training plans for athletes.**

In this paper, we propose the use of Automated Planning techniques for generating individual training plans, which consist of exercises the athlete has to perform during training, given the athlete's current performance, period of time, and target performance that should be achieved. Our experimental analysis, which considers general training of kickboxers, shows that apart of considerable less planning time, training plans automatically generated by the proposed approach are more detailed and individualised than plans prepared manually by an expert coach.

I. Introduction

In the last decades, performance of athletes developed beyond all expectations and predictions. Old records, which were considered unbreakable are nowadays reached even by amateurs during their training units. This has been made possible through better nutrition and improved training methods [1]. In all sports, the key to reaching high-level performance lies in the athletes' preparation in training. Without proper training planning and corresponding training execution, athletes cannot perform on their highest level [2]. Because of its complexity and importance, training planning is a well-known problem in the sports domain, and only a limited number of top-level coaches have the ability and resources to produce training plans of the quality that would enable their athletes to perform on their very best level.

Training planning is a highly demanding process that requires a significant portion of time, knowledge and a deep understanding of athletes' performance. Further, planning is influenced by a multitude of factors that vary according to different sports, which adds to the planning complexity. These factors include aspects such as athletes' predispositions, athletes' health conditions, competition goals, and even weather conditions [3]. The complexity and vast amount of variables to consider makes training planning a highly complicated process. This often results in an extensive simplification of the planning process (or even abandoning it at all) that relies on basic training rules and lacks an individual approach. In other words, a training plan is often devised with limited resources and distributed to all athletes of a training group. This is undesirable as sport performance improvement was observed when a variety of periodization strategies were used over a longer period of time [4].

This paper exploits Automated Planning as a useful tool for assisting coaches in developing individual training plans for athletes. We create a planning domain model that is used to automate generation of training plans for athletes, specifically for general training period in which athletes improve their physical skills. Although our primary focus is on kickboxing, we believe that our approach can be applicable, possibly with small modifications, for the majority of physical sports. Generally speaking, the model introduced in this paper focuses on planning exercises for a period of time such that athletes' attributes (e.g. strength, endurance) are expected to improve to a required level.

In order to evaluate our model, we have obtained three manually crafted plans provided by Alois Škeřík, a Czech national kick-boxing coach with 17 years of experience. Then, we automatically generated nine training plans that corresponded to the settings of coach's plans and, additionally, considered three types of athletes (according to their level). Generated plans were compared to manually crafted plans demonstrating their higher level of detail as well as their focus on individual athlete needs. The feedback of the coach confirmed that our method besides saving a lot of his efforts in plan preparation generates good quality training plans.

II. Automated Planning Background

Automated Planning belongs to the area of Artificial Intelligence and can be understood as the reasoning side of acting [5]. Automated Planning deals with the problem of finding partially or totally ordered sequences of actions, called plans, that transform the environment from its initial state to a desired goal state. These plans can be executed by artificial entities (e.g. robots) or by humans. Plans are often non-trivial and thus they capture sophisticated deliberative behaviour that aims at longer-term goals.

Domain-independent planning provides a large collection of planners, generic solvers, that accept a planning task description in a language such as PDDL [6] (an action language [7]) and returns a plan, a solution of the planning task (if it exists). Therefore, these planners can be understood as black-boxes and in order to operate them one has to generate a planning task description (in the required language) and then process the output plan.

A. Numerical Planning

Automated Planning can deal with different levels of expressiveness (e.g. classical planning, temporal planning, conformant planning). In this work, we exploit *Numerical Planning*, which is a subclass of Automated Planning that uses first order logic predicates (as classical planning) and numeric fluents to describe the environment and reasons in a deterministic and fully observable environment. *Actions* are specified via their *preconditions* which are logical expressions that must hold in order to make the action executable, and *effects* which are sets of literals or fluent assignments that take place when the action is executed. A *Planning Domain Model* consists of *first order logic predicates*, *numeric fluents* and *actions*. A *Planning Problem Description* consists of a set of *objects*, an *initial state* (a set of grounded predicates and fluent assignments), and a set of *goals* (logical expressions). A *plan* is a sequence of actions such that executing these actions in the given order (it must always be possible) transforms the environment from the initial state to a state with all goal formulas being satisfied (i.e. a goal state).

Noteworthy, numerical planning provides sequences of actions (plans) without explicit consideration of a time element. Although reasoning with time, which is a part of athlete training planning, is not explicitly possible in Numerical Planning, we can model necessary time aspects as objects and predicates and thus exploit classical planning. Hereinafter, we will use notation from PDDL [6]. An atomic expression of the form (name ?var1 ?var2 ... ?varn) denotes either a predicate or a numeric fluent distinguished by a unique name and a list of free variables (arguments) var1, var2,..., varn.

III. Sports Domain

Professional sport is primarily concerned with reaching the best possible performance in a particular discipline. Essentially, to achieve a great performance during different competitions, athletes have to adequately train long before a competition takes place. Professional athletes are typically guided by coaches, who provide them with knowledge in the specific sport discipline that is exploited for preparing athletes physically, tactically and psychologically.

Training in sports consists of a set of exercises, which are performed by athletes in preparation for competitions. To be able to get the best of training, it is necessary to carry out the exercises in a precise manner. So exercises have to be carefully planned to achieve the desired performance.

A. Training Planning

Kassa [8] describes the annual training plan as a tool used by coaches, which serves as a base for all scheduled training activities over a year. Training plans are periodical and an athlete's training year (macrocycle) is often divided into manageable training periods [9]. These periods are focused on the development of different abilities such as strength, endurance, speed, energy systems, technique, and tactic [10].

The generation of a training plan is usually divided into a number of steps: (i) information gathering, (ii) analysis of previously executed plan(s), (iii) athletes' performance assessment, (iv) set the main events (competitions) of a year, (v) identify phases, and outline objectives of each phase, (vi) determine activities of each phase, (vii) identify exercise volume intensity and recovery time within a season, (viii) determine a total number of training hours to be complete, (ix) identify appropriate training units (exercises) for each phase.

In summary, for getting a successful training plan, one has to assess the current athlete's performance, skills and abilities, determine desirable outcomes (ability, skill and performance improvement) in given periods of time, and design exercises (training units) the athlete has to perform to achieve the required improvements.

B. Performance Evaluation

Performance is a goal-directed set of movements, and the process of its evaluating and analysing an athlete execution of a specific task, as well as the level of skills involved in the task [11]. That said, there is a need to evaluate performance in all sports as it is used for determination of competitions' winners, and also for sport training improvement. One of the main purposes of performance evaluation (PE) is to obtain sport specific data, which are analysed for detecting errors in the training process and adopt corrective actions [12].

Higgins [13] views PE as a complex process that includes numerous stages, which are: (i) describing what should happen, (ii) describing what has happened, (iii) comparing expectations with results, (iv) taking corrective actions, if needed. Contributions to the view of Higgins' PE have been made by Fairs [14], who described five steps in performance evaluation: (i) data collection, (ii) diagnostics, (iii) prescribed plan of actions, (iv) implementation, (v) evaluation. The process of PE typically includes collection and analysis of a large amount of biased information about an athlete's performance. According to Fairs, data collection is the fact-finding part of the PE process, where data is obtained without making any conclusion or interpretation. Fairs claims that data collected in this step can include both objective and subjective metrics and measures. Subjective data is usually provided by an athlete, while objective data is collected by an evaluator using specific equipment for explicit measurement. Qualitative analysis of sports performance is based on a visual observation of human motion. As such analysis depends on experience of human evaluators, it is prone to errors as it depends on getting a clear picture of joint movements as they occur, which can be difficult in some situations [15]. In contrast, the quantitative analysis retrieves objective data, which has the form of a motion biochemical profile that is analysed in a later stage [12]. However, this method is extremely time-consuming and hence biomechanical quantification is a manual process.

It is therefore not surprising that numerous computer-based systems have been developed to increase the speed and quality of performance evaluation [12]. A substantial number of these systems are visual-based, i.e., they capture the complete athlete motion into digital form and afterwards analyse it (e.g., by Artificial Intelligence techniques). However, the sports domain lacks formal characterisations of attributes concerning the sports science. One of the possible directions is mathematical modelling that can be used for analysing responses to physical training and thus for predicting of training program outcomes [16]. Our approach is inspired by Busso's and Thomas' work [16] albeit simplified in order to comply with requirements of our planning domain model.

IV. Domain Specification

The fundamental concept for the sports domain depends on three main aspects, which are *physical*, *technical*, and *tactical* performance. This paper's primary focus is on the physical aspect because in the majority of sports the overall athletes' performance depends mainly on their physical abilities, which, consequently, also influences technical and tactical performance.

The physical abilities are measured in two main areas: *energy systems* and *muscle abilities*. Muscle abilities are represented by *strength*, *endurance*, and *explosiveness*, as these attributes represent aspects that can influence the athletes' performance in a given sport [17].

In our model, we consider three body parts, namely *upper limbs*, *lower limbs* and *mid-body* for which muscle abilities are measured. Noticeably, we do not represent each muscle individually but rather groups of muscles that have similar functionality. For planning purposes, muscle abilities have to be quantified: each attribute (for considered muscle ability and corresponding body part) has an associated numerical value. The value of attributes can be determined by conducting laboratory and/or field-based tests, which are routinely used to evaluate athletes' physical performance, particularly to create the training plans or to assess the impact of training. The main issue of this testing approach is that it does not provide any appropriate scale that would provide, at the same time, numerical values quantifying athletes' attributes (or abilities) as well as a relative comparison with other athletes. Furthermore, in order to generate training plans, we require to accurately quantify effects of exercises athletes have to perform during their training period. For dealing with the aforementioned issues, here we exploit the notion of *test battery*. A test battery is a set of tests, performed by a number of athletes competing in the same sport, used for assessing and prediction of sportsman performance [18]. These tests provide quantified performance in a given time (e.g. number of push-ups per minute). Hence, the test battery provides a set of values that determine a current state of required attributes of considered body parts (e.g. maximal strength, endurance, explosiveness). Further, to provide the most accurate comparison between athletes there is a need to categorized athletes into groups with similar height, weight, age, and gender.

Based on the measured results, it is then possible to determine the range of values the considered attribute can have. We set the range of values to be between -100 to 100. Specifically, the range is $[-100, 0]$ if the result of the battery test falls within "unable to perform" and "the bottom-line result in the category", and $[0, 100]$ if the result of the battery test falls within "the bottom-line result in the category" and "the top result in the category". Noticeably, these results are based on approximation (depends on other athletes' performance), which means that with increasing number of iterations, it is reasonable to expect that the results will gradually improve their precision. The calculation of the value of the attribute is done as follows. Let r be a result of the battery test, y_b be equal to the top result in the given category, and y_w be the approximate bottom-line result in the given category. Both y_b and y_w are values that are reused and improved with number of testing iterations. The value of the attribute is calculated by the following expressions:

$$x = 100, \text{ if } r \geq y_b$$

$$x = 100\frac{(r - y_w)}{(y_b - y_w)}, \text{ if } r \geq y_w$$

$$x = 100(\frac{r}{y_w} - 1), \text{ if } r < y_w$$

To give a better explanation of attribute value determination, a push-up test can serve as an example. Three testing "samples" are provided in order to demonstrate how the results of test battery are translated into attribute values. The push-up test (maximum push-ups in one go) provides us with a result of an endurance ability for the upper limbs muscles under load. According to the above categorization, we consider three results: 0 push-ups (the athlete was not able to perform the test), 20 push-ups as y_w (the bottom-line result in the considered category), 100 push-ups as y_b (the top result in the category). If the athlete's performance in the push-up test is in $[0, 20)$, then the attribute value will be in $[-100, 0]$. If the athlete's performance in the push-up test is $[20, 100]$, then the attribute value will be in range $[0, 100]$.

Three athletes that have similar body structure (for instance, male approximately 80kg of body weight, and 185cm of height) may have a different performance level (in our example, low, medium and high performance level). Their results in the push-up test are then translated into the value of upper limbs muscle endurance as follows.

1) Subject with higher physical performance level:
   Maximum push-ups: 80 ⇒ Upper limbs endurance: 75
2) Subject with medium physical performance level:
   Maximum push-ups: 60 ⇒ Upper limbs endurance: 50
3) Subject with lower physical performance level:
   Maximum push-ups: 15 ⇒ Upper limbs endurance: -25

For determining the value of attributes referring to *energy systems* abilities, an analogous approach is exploited. In this case, however, the attributes are related to the whole athlete's body (and not to parts of it).

Effects of exercises athletes have to perform during training are determined by average improvement of athletes' attributes in the given category. Again, this is an approximate method

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0: (STRENGTHENDURANCETU SLOT3 UPPER_LIMBS SLOT2 SLOT4 W1) [1]
0: (AGILITYTU SLOT1 DUMMY_SLOT SLOT2 W1) [1]
0: (INTERVALTU SLOT4 LOWER_LIMBS SLOT3 SLOT5 W1) [1]
0: (AEROBICTU SLOT2 SLOT1 SLOT3 W1) [1]
0: (CROSSTU SLOT5 UPPER_LIMBS SLOT4 SLOT6 W1) [1]

T_Day:1 Week 1: AGILITY TU
T_Day:2 Week 1: AEROBIC TU
T_Day:3 Week 1: STRENGTH & ENDURANCE TU UPPER LIMBS
T_Day:4 Week 1: INTERVAL TU LOWER LIMBS
T_Day:5 Week 1: CROSS TU UPPER LIMBS
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Fig. 1. An example of a automatically generated plan for week 1 by the LPG-td planner (top) and its translation into a chronologically ordered training plan (bottom). Important action arguments are emphasised in italics.

whose accuracy depends on the group of athletes in the category. For example, if a "circuit" exercise is performed for upper limbs, then the anticipated improvement of upper limbs endurance is 1.1.

A. Formal Specification of the Proposed Model

Formal conceptualization of the domain model follows the aim: generate training plans, i.e., which exercises and when the athlete has to perform them, given the period of time and target athlete's attributes. We consider *strength*, *endurance* and *explosiveness* for each body part (i.e., upper and lower limbs, and mid body), and *anaerobic* and *aerobic* systems (for the whole athlete's body). These attributes are represented as numeric fluents.

Each exercise can be scheduled into one or more *slots* (no slot can have more than one scheduled exercise), represented by an (action-allocated ?action ?slot) predicate. If a slot is free, then a predicate (free ?slot) represents this. A training *week* consists of several slots (might vary for different weeks), represented by a predicate (slot-in-week ?slot ?week). Adjacency of slots (used for avoiding consecutive exercises of the same type) is represented by a predicate (adjacent ?slot-prev ?slot ?slot-next).

The model considers 11 actions, where each action corresponds to one exercise method, namely: *Agility*, *Circuit*, *MaximumSpeed*, *Aerobic*, *Anaerobic*, *MaximumStrength*, *Interval*, *Cross*, *Fartlek*, *Polymetrics* and *StrengthEndurance*. Each action (or exercise) has a limit of how many times it can be scheduled for a single week. This numerical constraint is represented by a numeric fluent (action-capacity ?action ?week). Notice that the limit can be different for different weeks.

For each exercise, except *Anaerobic* and *MaximumSpeed*, it is the case that the same type of exercise cannot be scheduled in adjacent slots. Generally speaking, preconditions of the actions corresponding to these exercises have the following structure. Assuming the corresponding exercise is scheduled to a ?slot in a week ?week, (free ?slot), (slot-in-week ?slot ?week) and (action-capacity ?action ?week) greater than zero must hold. To satisfy the "non-adjacency constraint", (adjacent ?slot-prev ?slot ?slot-next), (not (action-allocated ?action ?slot-prev)) and (not (action-allocated ?action ?slot-next)) must hold as well. Effects of the actions consist of (not (free ?slot)), (action-allocated ?action ?slot), decreasing (action-capacity ?action ?week) by 1, and increasing the corresponding athlete's attributes.

The *Anaerobic* action is encoded analogously but without the "non-adjacency constraint" (i.e., anaerobic exercises can be done in a row). The *MaximumSpeed* action has to be scheduled for two adjacent slots leaving the next slot unallocated (i.e., no exercise can be scheduled on that slot). The precondition is modified such that ?slot,?slot-prev and ?slot-next has to be in the same week (?week)) and free. Apart of increasing the corresponding athlete's attributes, the effects make ?slot,?slot-prev and ?slot-next "not free" and allocate *MaximumSpeed* action on ?slot,?slot-prev.

For an individual athlete, we have to specify a problem description (note that the domain model is the same for a class of athletes performing the same type of training). The initial state has to define "schedule constraints", i.e., the adjacent, slot-in-week and free predicates for all considered slots (or training days). Also, maximum numbers of particular types of exercises per week, i.e., the values of the action-capacity fluent for each action and week, have to be specified in the initial state. Then, the initial values of athlete's attributes are specified in the initial state. Goals, to be achieved by the automatically generated training plan, specify the minimum desired values of the athlete's attributes that the athlete should achieve after the training (note that plans leading to higher attribute values are permitted). The domain model (in PDDL) can be found at https://github.com/skerovs/SMC2018SportDomain.

With the domain model and problem specification, we can use off-the-shelf planners to generate a plan. The plan might not be chronologically ordered (according to slots or training days). On the other hand, the plan contains a full information what exercise is scheduled when, so it is straightforward to generate a chronological training plan from it. An example of translation of an automatically generated plan into a chronologically ordered training plan in depicted in Figure 1.

V. Experiments and Evaluation

The aim of the experiments is to show that our automated-planning-based method for generating athletes' training plans (for general training) generates plans that are more detailed and individualised than those made by an expert. Besides this aspect, the method can generate plans in a short time, hence can considerably reduce the expert's efforts.

For evaluating our method for generating athletes' training plans, we used manually made plans obtained from a Czech national kick-boxing coach as a baseline. The coach provided 3 plans for a general preparation period of 9 weeks that have been used in the past. We have specified 9 planning problems that reflected the settings of the coach's plans and, additionally, considered different athletes' performance, i.e., entry-, mid-, and top-level, since our aim is to generate individualised plans while the coach's plans were created for a group of athletes.

Given the planning problems (the domain model and problem specification), we generated plans by using the well-known LPG planner [19] because it achieves good perfor-

TABLE I
AUTOMATED VS EXPERT (COACH) PLAN GENERATION

	Automated	Domain Expert
# of exercise types	11	5
Search time	0.1 - 18.6 sec	3 - 5 hours

TABLE II
3 WEEKS OF EXPERT'S PLAN FOR GROUP OF ATHLETES (STAD-STADIUM, REH-REHERSAL, TECH&RUN-TECHNIQUE AND RUNNING)

	WEEK 1	WEEK 2	WEEK 3
Mo	Tech&Run, Stad.	Dev, Gym	Dev, Gym
Tu	Tech&Run, Gym	Tech&Run, Stad	Tech&Run, Stad
We	Rest	Rest	Rest
Th	Tech&Run, Stad	Tech&Run, Stad	Tech&Run, Stad
Fr	Reh in pairs, Gym	Reh in pairs, Gym	Reh. in pairs, Gym

mance in our domain. The planner was run on a machine equipped with an i5-6200U 2.3GHz 64-bit CPU, 8GB RAM, and Ubuntu 17.04 operating system.

Table I gives an overview of the automated and domain expert's planning process, i.e., how easy/hard it is to generate training plans and how detailed these plans are. According to the coach, creating a single training plan would require several hours to complete. In contrast, our automated method generates a single training plan in the order of seconds. Moreover, the expert's plans are less detailed, as they consider only 5 types of exercises, while ours do 11. That said, it is not feasible for domain experts (coaches) to create individual (or individualised) training plans given the effort that manual planning requires. Hence, they often produce (very) general plans and decide what exercise to do next "on the fly".

Noteworthy, the performance evaluation of each athlete (before and during a training period) is the most expensive part for obtaining necessary inputs for both automated and manual training plan generation. The only difference is in quantifying athletes' attributes, which is necessary for our method. However, if we have results from performance evaluation of a given athlete, his/her attributes can be easily calculated (as described in Section IV).

A. Plan Comparison

To shed light into how an expert's and automatically generated plans look like, we have chosen one expert's plan (out of three) and its corresponding generated plans for entry-, mid- and top-level athletes. The first three weeks of the expert's plan are depicted in Table II and the first three weeks of its corresponding generated counterpart in Table III.

From the expert's plan (Table II) we can observe that it provides information about time, place and the kind of Training Unit (TU). As an example we can see the action "Technique and Running", which provides only very general information about what the given TU will be about. Consequently, the expert's plans do not inherently reason about performance of particular athletes but they rather indicate when and where the athletes have to be present and what kind of TU they should expect. In other words, the decision about what exercise will actually take place is made "on the fly" by coaches based on their expertise and assessment of the athletes' current performance.

TABLE III
3 WEEKS OF GENERATED PLANS FOR ENTRY-, MID- AND TOP-LEVEL ATHLETES (UL-UPPER LIMBS, LL-LOWER LIMBS, MB-MIDDLE BODY)

	WEEK 1	WEEK 2	WEEK 3
	ENTRY Level Athlete		
Mo	Cross	Strength Endu. MB	Circuit MB
Tu	Polymetrics UL	Aerobic	Cross
We	Strength Endu. UL	Cross	Aerobic
Th	Agility	Fartlek	Fartlek
Fr	Fartlek	Polymetrics MB	Strength Endu. MB
	MID Level Athlete		
Mo	Agility	Strength Endu. LL	Aerobic
Tu	Aerobic	Polymetrics MB	Fartlek
We	Strength Endu. UL	Circuit MB	Polymetrics UL
Th	Interval	Aerobic	Circuit UL
Fr	Cross	Agility	Interval
	TOP Level Athlete		
Mo	Strength Endu. UL	Circuit LL	Polymetrics UL
Tu	Fartlek	Aerobic	Fartlek
We	Circuit LL	Strength Endu. UL	Anaerobic LL
Th	Cross	Interval	Strenght Endu. LL
Fr	Polymetrics LL	Cross	Interval

In contrast to the expert's plans, the automatically generated plans by our Automated Planning based method (Table III) provide details about specific exercises that should take place in given time slots. The generated plans consider athletes' observed performance prior to training as well as anticipated effects of the particular exercises on their performance improvement, more specifically, what attributes that characterise athletes' performance will be adjusted. Moreover, our method is designed for generating individual training plans, so training can be tailored for individual needs of particular athletes. This becomes clear in Table III, where partial training plans (for first three weeks) are shown for three different athletes, the entry-, mid- and top-level ones. These (partial) plans correspond with the expert's (partial) plan as shown in Table II. Both expert's and generated plans follow the same objective – the general training of kickboxers.

Taking a closer look at the differences of generated plans for three different athletes, we can observe, for example, that the entry- and mid-level athletes require focusing more on improving their aerobic system, and their strength and endurance. Top-level athletes, on the other hand, need to sustain their current level of aerobic system, and need to further develop their anaerobic system, explosiveness and maximal strength. To illustrate the differences we can focus on exercises "Aerobic", "Anaerobic" and "Fartlek". Fartlek, for instance, consists of long distance running, in which the running speed varies. Consequently, Fartlek improves the aerobic system and partially also the anaerobic system. The focus on improving the aerobic system of the entry- and mid-level athletes can be demonstrated by having (in the first three weeks) 2 aerobic and 3 fartlek exercises, or 3 aerobic and 2 fartlek exercises, respectively. On the other hand, the top-level athletes have 1 aerobic, 2 fartlek and 1 anaerobic exercises (in the first three weeks), which shows a higher focus on their anaerobic system. As a further example, we can consider the "Strength Endurance MB" exercise, which focuses on improving mid body strength and endurance attributes. This exercise includes sit-ups, barbell roll-outs, leg raises, etc. The "Strength Endurance MB" exercise is useful especially for the entry-level athletes and, therefore, they have 2 of them in the first three weeks of training.

B. Expert's Feedback and Discussion

We have shown that by using our method we can generate more detailed training plans for (individual) athletes than the expert (coach) and in much less time. To assess the quality of the generated plans, we have consulted with the domain expert, Alois Škeřík, who is a coach of the Czech national kickboxing team. The expert has reviewed the plans and provided us with feedback. According to the expert's opinion, the plans are of a good quality and, hence, if applied in practice, they can improve the athlete training process, possibly resulting in better athletes' performance than could be achieved by traditional training. The expert also highlighted the time saving aspect, so he can save a lot of time (hours per athlete) that he had to spent preparing training plans.

The expert expressed concerns of managing a larger group of athletes with individual training plans because each athlete might do a different exercise at time. To address this issue, we could generate plans for groups of athletes (e.g. entry-, mid- and top-level). In the future, we plan to integrate coach and space/facility constraints into our method.

Another interesting aspect of our method is its flexibility. The generated training plans also provide information how athletes' attributes are expected to develop in time. If, for example, we observe that after two weeks of training, an athlete's actual performance considerably differs from the expected one, we can specify a new planning problem (from the third week onwards and considering the actual athlete's performance) and generate a new training plan. In other words, we can easily adapt plans according to observed athletes' performance even during the training period.

VI. CONCLUSION

In this paper, we have exploited automated planning in a real-world scenario concerning generating plans for general training for professional athletes. Moreover, we have developed a new technique for quantifying athletes' general performance that is an essential part of the approach. We used 9 case studies (actual athletes) and three plans manually generated by an expert to evaluate our approach. We compared in more detail one expert's plan with its three automatically generated counterparts (training plans for entry-, mid- and top-level athletes). The results indicate that the automatically generated plans are more detailed, individual, realistic, and that their generation can save a lot of experts' time.

As future research, we plan to consider additional constraints such as coaches and/or facilities availability. Also, we plan to apply our method (or its variant) for generating training plans for tactical exercises for kick-boxing and later, possibly, to generate training plans for other sports. There is also intention to explore possibility of using mathematical modelling that could provide elegant approach for confirming validity of our generated plans. Last but not least, we plan to undertake a case study in which actual athletes will perform exercises from generated plans that would provide a better understanding of strengths and weaknesses of our approach, particularly the accuracy of our model.

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